NASA TECHNICAL NOTE

NASA TN D-8253 c.1

NASA TN D-8253

METEOROLOGICAL ADJUSTMENT OF YEARLY MEAN VALUES FOR AIR POLLUTANT CONCENTRATION COMPARISONS

Steven M. Sidik and Harold E. Neustadter

Lewis Research Center

Cleveland, Ohio 44135

NATIONAL AERONAUTICS AND SPACE ADMINISTRATION • WASHINGTON, D. C. • JULY 1976

1. Report No. NASA TN D-8253	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle METEOROLOGICAL ADJUSTMENT OF YEARLY MEAN VALUES FOR AIR POLLUTANT CONCENTRATION COMPARISONS		5. Report Date July 1976
		6. Performing Organization Code
7. Author(s) Steven M. Sidik and Harold E. Neustadter		8. Performing Organization Report No. E-8628
		10. Work Unit No. 176-90
9. Performing Organization Name and Address Lewis Research Center National Aeronautics and Space Administration Cleveland, Ohio 44135		11. Contract or Grant No.
		13. Type of Report and Period Covered Technical Note
12. Sponsoring Agency Name and Address National Aeronautics and Space Administration Washington, D.C. 20546		14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

Using multiple linear regression analysis we derive models which estimate mean concentrations of Total Suspended Particulate (TSP), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2) as a function of several meteorologic variables, two rough economic indicators, and a simple trend in time. Considered are 24-hour averaged concentrations measured in Cleveland, Ohio, from 1967 to 1972 (approximately 450 observations for TSP and 400 observations at 13 sites for SO_2 and NO_2) by the municipal Division of Air Pollution Control. Meteorologic data were obtained from the National Weather Service and do not include inversion heights. This is representative of data typically available to a local pollution-control agency. The goodness of fit of the estimated models is partially reflected by the squared coefficient of multiple correlation which indicates that, at the various sampling stations, the models accounted for about 23 to 47 percent of the total variance of the observed TSP concentrations. If the resulting model equations are used in place of simple overall means of the observed concentrations, there is about a 20 percent improvement in either (1) predicting mean concentrations for specified meteorological conditions or (2) adjusting successive yearly averages to allow for comparisons devoid of meteorological effects. This improvement can be obtained with no additional cost other than a moderate effort at statistical analysis. An application to source identification is presented using regression coefficients of wind velocity predictor variables.

17. Key Words (Suggested by Author(s)) Meteorological adjustment Source identification Regression analysis Air pollution		18. Distribution Statement Unclassified - unlimited	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 42	22. Price* $4.00

* For sale by the National Technical Information Service, Springfield, Virginia 22161

METEOROLOGICAL ADJUSTMENT OF YEARLY MEAN VALUES FOR AIR POLLUTANT CONCENTRATION COMPARISONS

by Steven M. Sidik and Harold E. Neustadter

Lewis Research Center

SUMMARY

This report presents an approach to interpretation of 24-hour averaged air pollutant measurements taken in compliance with U.S. Environmental Protection Agency guidelines when analyzed in conjunction with such meteorological data as may be readily obtained from the National Weather Service. The specific examples considered are Total Suspended Particulates (TSP), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2) in Cleveland, Ohio, for which some monitoring has been performed by the municipality since 1967, initially every sixth day and currently every third day.

We fit linear regression models to pollutant concentrations using the following combinations of meteorologic variables as predictors: daily delta temperature (defined as the maximum temperature minus the minimum) and its first difference; daily minimum temperature and its first and second differences; daily average barometric pressure; daily total precipitation (water equivalent in in.); and daily resultant wind velocity.

We included two rough indicators of economic activity and allowed for the existence of both a linear "drift" in time and a seasonal component with a period of 1 year.

The goodness of fit of the estimated models to the data is partially reflected by the squared coefficient of multiple correlation, indicating that at the various sampling stations the models accounted for about 23 to 47 percent of the total variance of observed TSP concentrations.

About a 20 percent improvement when using these equations in place of simple mean observed values is obtained when (1) predicting mean concentrations for specified meteorological conditions or (2) comparing yearly averages after being adjusted so as to remove meteorological effects.

We also present an application to source identification using regression coefficients of wind velocity predictor variables.

INTRODUCTION

Since the adoption of ambient air quality standards by the U.S. Environmental Protection Agency (USEPA), increasing numbers of communities have become involved in the abatement and/or control of air pollution. The meaningful planning and management of such activities requires that the people making decisions have available information defining the levels and trends in ambient air quality. Such questions as: "Is the air getting cleaner (dirtier)?" or "What might next year's air quality be?" must be answered. In general, the answers must be obtained from existing data from ambient air quality monitoring programs. Unfortunately, these data do not directly relate to the aforementioned questions. Abatement and control policies are concerned with pollutant emissions, whereas the observed ambient pollutant levels are significantly affected by meteorological variability. Weather is a dominant factor in determining pollution transport, dilution, washout, and so forth. Thus, if ambient air quality data are to be applied beyond the question of how dirty (clean) it was when the measurements were made, compensation must be made for this meteorological variability.

This need for meteorological adjustment has long been recognized. Studies of the relation between pollutant concentrations and weather have generally considered smaller parts of the total problem. For example, Turner (ref. 1) examined the relationship between two pollutants (SO_2 and TSP as indicated by a soiling index) and three meteorological variables (mean wind speed, mean wind stability, and degree days) by linear regression analysis. There have also been several studies of the washout of certain pollutants by precipitation (Hales (ref. 2); Dana, Hales, and Wolf (ref. 3)). Most studies of the effect of wind speed and direction have concentrated on Gaussian plume diffusion models (ref. 4). Such models require a knowledge of source strength, wind speed, mixing heights, and so forth. Yet other studies have considered the analysis of multiple time series where one series consists of the pollutant concentrations and the other series consist of meteorological variables (temperature, wind speed, etc. (ref. 5)). Time series methods generally require (effectively) continuous pollutant data and/or (effectively) continuous meteorological data.

This report is directed to the typical field agency working with limited resources and following monitoring guidelines equivalent to those set by the USEPA (e.g., 24-hour averaged sampling once every 6 days). This led us to place restrictions on the data set to be considered. Namely, the data had to be either that which a local agency would normally generate or which it could obtain with a minimum of effort and cost. The main consequences of this restriction were that we used non-continuous pollution data and have no measured mixing heights or inversion layers in the meteorological data.

The following sections describe the application of linear regression modeling to estimating pollutant concentrations using the following combinations of variables as predictors: daily delta temperature (defined as the maximum temperature minus the minimum temperature) and its first difference; daily minimum temperature and its first and second differences; daily average barometric pressure; daily total precipitation (water equivalent in in.); and daily resultant wind velocity. The model also includes two rough indicators of economic activity and allows for the existence of both a linear "drift" in time and a seasonal component with a period of 1 year.

The remaining sections discuss the interpretation and application of the models developed, as well as the goodness of fit and sources of error. As a result of our study, it is clear that a significant enhancement of the value and relevance of the air quality data currently being amassed can be obtained with no additional cost other than a moderate effort at statistical analysis.

POLLUTANT CONCENTRATION DATA

The Cleveland Division of Air Pollution Control has taken 24-hour averaged air quality samplings of TSP since January 1967, and of NO_2 and SO_2 since January 1968. The present geographic deployment of the sampling sites is shown in figure 1. The meandering heavy line in the center of the city is the Cuyahoga River, about which is clustered most of the region's heavy industry.

Of the 21 monitoring stations, 18 currently monitor all three pollutants while the remaining three (stations 16, 18, 20) monitor TSP only. Seventeen of these stations have been in operation since 1967. Stations 2, 4, 12, and 15 have undergone relocation since their initial installation. However, because of the proximity of their present sites to their former sites, we have assumed that essentially the same environment has been measured throughout the period covered in this study. Currently, the air is sampled every third day, although sampling frequency has varied over the years and initially was once a week. Because some of these sites lack sufficient data, we present results only for 19 sites for TSP and 13 sites for SO_2 and NO_2.

Summaries of the air pollution data used for this study, including tabulations of means, standard deviations and goodness of fit to lognormality on an annual basis have been reported earlier (ref. 6).

The sampling method for TSP is high volume air samping using glass fiber filters. A previously published study showed that, for such high volume air sampling of TSP in Cleveland, approximate 95 percent confidence limits on the errors introduced by filters and samplers were about 12 percent high to 11 percent low (ref. 7).

The sampling method for NO_2 was the Jacobs-Hocheiser method (ref. 8) which was, at that time, the USEPA-sanctioned method. However, this method has since been discarded because of the recent awareness that the response to NO_2 is nonlinear. This feature is especially detrimental when the sampling time is sufficiently long so that a single sample may reflect the cumulative effects of widely varying NO_2 concentrations.

Sulfur dioxide was sampled by a West-Gaeke colorimetric technique (ref. 8). Under the laboratory practices (i.e., wavelength, temperature, and so forth) used in Cleveland until June 1972, the approximate 95 percent confidence limits on SO_2 concentrations were about ± 20 percent for values above 35 nanograms per cubic meter. Any value below that was retained as reported, but confidence in the value is minimal. From August 1972 until June 1975 there was a transition to a more carefully controlled test resulting in better quality control. However, during this changeover period, the reproducibility of the data was erratic.

Obviously, for these three pollutants, we place most credibility in TSP. Hence, our analyses and discussions concentrate primarily on TSP. The SO_2 and NO_2 data are included primarily to display their qualitative rather than quantitative features.

REGRESSION ANALYSIS

Models and Method

The statistical modeling discussed in this report leads to the development of equations which may be used (1) to predict mean pollutant concentrations for given meteorological conditions, and (2) to compute pollution concentrations adjusted for meteorological conditions. Such models could also contribute to a better understanding of how certain meteorologic variables affect daily pollutant concentrations.

The method chosen for accomplishing this was multiple linear regression analysis which is explained in such texts as Searle (ref. 9), Draper and Smith (ref. 10), and Daniel and Wood (ref. 11).

We assume models of the general form

$$y_i = \beta_0 + \sum \beta_j x_{ij} + \varepsilon_i \tag{1}$$

where

y_i — i^{th} observed pollutant concentration or some transformed value of that concentration. In this report we use $y = \log(\text{TSP})$, $y = \sqrt{NO_2}$, and $y = \sqrt{SO_2}$. The motivations for choosing these specific transformations are discussed in the next paragraph.

x_{ij} — observed value of j^{th} predictor variable (i.e., meteorologic or economic) for i^{th} observation. The particular predictor variables (such as barometric pressure) used are presented in table I and discussed in detail in the appendix.

β_0 — unknown intercept values

β_j — unknown coefficients (slopes) which are to be estimated. Multiple linear regression as used here estimates these unknown coefficients by the least squares method. (Estimated values are denoted by $\hat{\beta}_j$).

ε_i — unobserved random error component. This random error is assumed to follow a normal distribution with a mean of zero and a standard deviation of σ which is unknown. We further assume that the ε_i are uncorrelated with each other.

The random error ε_i will include, among other things, errors of measurement of the concentrations, inherent variability of concentration because of varying emission rates and/or atmospheric instability, inadequacies in the model, and to some extent the errors of measurement of the predictor variables. Our data base consists primarily of 24-hour averaged concentrations at 3-day intervals. A previous study (ref. 12) found that concentrations observed every 3 days have a very low correlation. Thus the assumption that the ε_i are uncorrelated is reasonable.

It should be noted that with daily pollutant values the errors in successive observations might not be uncorrelated and linear regression would not be appropriate without some modification. A more appropriate method might consist of analysis of multiple time series.

The choice of transformation of the observed pollutant concentrations is somewhat tied to the model and the distributional assumptions made about the error component. In this study, we fit linear models of the form of equation (1) and for each pollutant at each station visually examined plots of the differences (residuals) defined by

$$\hat{\varepsilon}_i = y_i - \hat{y}_i = y_i - \hat{\beta}_0 - \sum \hat{\beta}_j x_{ij}$$

Residual plots of the ε_i using the transformations log(TSP), $\sqrt{NO_2}$, and $\sqrt{SO_2}$ appeared, upon visual inspection, to generate distributions that approximated normal distributions with a mean of zero.

Basic Predictor Variables

We are aware that, in most instances, air quality monitoring networks do not routinely perform meteorological monitoring. Nor do they have the resources for such monitoring no matter how desirable it might be to have such information. Therefore, any analytical method which would be generally applicable must not require any additional monitoring effort. Recognizing this, we have constrained our use of meteorological variables to those which are readily available from the National Weather Service (NWS). Specifically, we used only variables listed on the Monthly Local Climatological Data Summary sheets. These are available from NOAA (Asheville, NC) as both printed sheets and punched cards (decks #345 and #939 form k). These variables include minimum and maximum temperature, average barometric pressure, total precipitation, and resultant wind velocity for each 24-hour midnight-to-midnight period.

In Cleveland, these data are measured at the Cleveland Hopkins Airport, which is in the southwest corner of the city (see fig. 1).

Two quite rough indicators of economic activity were incorporated. These are (1) whether the day of observation is a workday or a nonworkday (defined as Saturday, Sunday, and Federal holidays), and (2) a weekly regional steel index (ref. 13).

Derived Variables and Estimated Coefficients

Pollutant concentrations at a given time and location are the result of emissions from various sources which have undergone transport and dispersion processes in the atmosphere. In general, for a fixed rate of emission from all sources, pollutant concentrations are inversely proportional to atmospheric mixing. The factors generally considered to control the degree of mixing are the effective mixing height, wind velocity, and wind stability (ref. 4). In most locations, however, the NWS does not routinely monitor mixing heights. Thus, this information has not been incorporated even though such measurements were made locally by the NWS for a period of 1 year.

To construct model equations which can predict pollutant concentrations for known meteorological conditions, we defined new predictor variables derived from those basic variables known or suspected to be related to atmospheric mixing. In constructing derived variables we were guided primarily by Holzworth's (ref. 14) qualitative account of large scale weather influences on air pollution concentrations.

Table I presents the 29 derived variables used in the predictive models. These variables, the rationale for their inclusion and the results are discussed in depth in the appendix. This model was fitted separately at each station and for each pollutant. Tables II to IV summarize the regression results for TSP, $\sqrt{NO_2}$, and $\sqrt{SO_2}$, respectively. It is a logical assumption that the form of the model should be the same at all stations, although the estimated coefficients might vary somewhat from station to station for a variety of reasons (e.g., slightly different meteorology due to local topography or "lake effects" or different placement with respect to the major sources in the area.)

Tables II to IV present (1) the estimated coefficients for each predictor variable, (2) the value of square of multiple correlation coefficient R^2, (3) the number of observations available for fitting, (4) the estimate of the error variance $\hat{\sigma}^2$ and error standard deviation $\hat{\sigma}$, and (5) the mean of the observed concentrations $\bar{y}$. The meaning and use of each of these quantities are discussed in the following sections.

Table II presents the regression summaries for log(TSP). There are 17 stations for each of which there are approximately 450 observations. Stations 20 and 21 have approximately 100 observations each and are retained for completeness but are not included in the detailed analyses of the appendix. Station 11 has fewer than 100 observations and has also not been included in the analysis. Station 13 is the only ground based sampling station (all other being on rooftops). It has been subjected to intermittent vandalism and has thus not been included.

Tables III and IV present the regression summaries for NO_2 and SO_2, respectively. Only 13 of the stations have sufficient data to be included in this study.

Meaning of Coefficients

The model equations we postulate are of the form

$$y = \beta_0 + \sum \beta_i x_i + \hat{\varepsilon}$$

The method of least squares provides estimates for the β_i which we denote as $\hat{\beta}_i$ and which specify the individual change in y which corresponds to a change in x_i. Suppose we consider the estimated function for log(TSP) at station 1. Suppose also that we are interested in comparing 2 days which differ only in the fact that the $\Delta T = x_1$ of day 2 is 10^o higher than the ΔT of day 1. The predicted values are then

$$\hat{y}_1 = \log(TSP_1) = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \ldots + \hat{\beta}_{29} x_{29}$$

and

$$\hat{y}_2 = \log(TSP_2) = \hat{\beta}_0 + \hat{\beta}_1 (x_1 + 10) + \ldots + \hat{\beta}_{29} x_{29}$$

Thus,

$$\log(TSP_2) - \log(TSP_2) = \hat{\beta}_1 (10)$$

or

$$\frac{TSP_2}{TSP_1} = 10^{\hat{\beta}_1 (10)}$$

Since $\hat{\beta}_1 = 0.010$, we find that this increase in ΔT of 10^o implies

$$\frac{TSP_2}{TSP_1} = 10^{(0.010)(10)} = 1.26$$

In other words, the increase in ΔT of 10^o implies an average increase of TSP concentration of 26 percent.

In general, then, for TSP a difference in predictor x_j from x_{1j} to x_{2j} implies that

$$\frac{TSP_2}{TSP_1} = 10^{\hat{\beta}_j(x_{2j} - x_{1j})}$$

from which we can estimate the percentage increase or decrease in TSP.

As further examples (at station 1), suppose we wish to determine the effect of an increase in barometric pressure x_6 of 0.3 inch. We find that

$$\frac{TSP_2}{TSP_1} = 10^{\hat{\beta}_6(0.3)} = 10^{(0.16)(0.3)} = 1.12$$

thus implying an average increase of 12 percent. Or suppose we wish to estimate the change in TSP concentration from September 13, 1967 (the date of first sample) to December 29, 1975 (the date of last sample). This is a period of 1935 days and hence

$$\frac{TSP_2}{TSP_1} = 10^{\hat{\beta}_{27}(19.35)} = 10^{(-0.0089)(19.35)} = 0.67$$

thus implying a 33 percent drop in concentration on the average.

The aforementioned procedure can be immediately extended to all the variables and all the stations with respect to TSP. A similar procedure can be used for the NO_2 and SO_2 concentrations except that the use of the square root transformation for these pollutants makes deriving percentage changes somewhat more tedious.

If a variable has no relation to concentration levels, then the coefficient of that variable is theoretically equal to zero. In general however, random fluctuations in the data will produce nonzero estimates even in the absence of a relation. Partial t-statistics (see Draper and Smith, ref. 10) can be computed for each $\hat{\beta}_i$ to infer whether or not its difference from zero is the result of such random fluctuation. In tables II, III, and IV each estimated coefficient $\hat{\beta}_i$ which has an associated partial t-statistic with absolute value greater than 1.70 is footnoted to indicate that it is significantly different from zero. This provides less than a 10 percent chance that such nonzero values resulted from random fluctuations in the data.

Goodness of Fit and Error Estimate

We have derived regression equations which estimate pollution concentrations from certain economic and meteorological variables.

The models were all based on linear relations, and we used the method of least squares to find the single best fitting model. An obvious question is: Just how well does it fit? One measure of the goodness of fit to the data is given by the quantity R^2, the proportion of the total variance of the transformed concentration that is accounted for by the regression equation. (It is also the square of the correlation coefficient between the observed y values and the concentrations calculated by the fitted model.) If $R^2 = 1.0$, this implies that the fitted model exactly predicts all of the observed y values. If $R^2 = 0.0$, this implies that the regression equation has absolutely no predictive value.

Table II shows that for TSP the R^2 values range from a low of 0.23 to a high of 0.47 (excluding stations 20 and 21) with most of the values near 0.40. In other words, the models account for from 23 percent to 47 percent of the total variance of the log(TSP) values.

Table II shows that for NO_2 the R^2 values range from a low of 0.17 to a high of 0.35. Table IV shows that the values for SO_2 range from 0.19 to 0.34. It is thus seen that log(TSP) values are fit slightly better than are the NO_2 and SO_2 values.

The model of equation (1) includes an error component which we have assumed follows a normal distribution with unknown variance σ^2. This error describes the inability of the model to exactly predict the observations. An estimate of σ^2 is provided by the residual mean square. If $\hat{y}_i$ denotes the predicted values based on the best fitting model, then the residual mean square is defined as

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n - 30}$$

where n is the sample size and 30 is the number of estimated coefficients. An estimate for σ, the standard deviation of the distribution of ε, is then the standard error of estimate defined by

$$\hat{\sigma} = \sqrt{\hat{\sigma}^2}$$

Table II shows that, for log(TSP), $\hat{\sigma}$ ranges from 0.140 to 0.233 with most values being around 0.160. The importance of $\hat{\sigma}$ to the problem of using the models to predict concentrations will be covered in the following section.

APPLICATIONS

Predictions from Fitted Models

The primary motivation of this work was to develop a method for making predictions. Actually, two different predictions are of interest. The first is the prediction (or estimate) of the <u>mean</u> pollutant concentration as a function of the predictor variables and the second is the prediction of a <u>single</u> further pollutant concentration. Both predictions result from inserting the specified values of the predictor variables (i.e., the x_i) into the estimating equation yielding

$$\hat{y} = \hat{\beta}_0 + \sum \hat{\beta}_i x_i$$

However, the uncertainties (standard deviations) associated with each application are very different.

The uncertainty in the prediction of the mean of the y's for specified x_i is a function only of the actual x and the uncertainty of the estimates $\hat{\beta}_i$. The estimated standard deviation of $\hat{y}$ when the x_i are all equal to the means of the x_i is $\hat{\sigma}/\sqrt{n}$. For the TSP data of station 1 we obtain a standard deviation of 0.170/

$\overline{382} = 0.0087$. Thus an approximate 95 percent confidence limit on $\hat{y}$ is

$$\hat{y} - (1.96)(0.0087) \leq \log(\text{TSP}) \leq \hat{y} + (1.96)(0.0087)$$

In terms of TSP directly this results in proportional limits of

$$10^{\pm(1.96)(0.0087)} = (1.04,\ 0.96)$$

or roughly ± 4 percent. Thus the regression equation itself is pretty well estimated. These confidence limits change with the x_i (see Draper and Smith (ref. 10) for details).

The uncertainty in a further predicted value includes not only the uncertainty in the regression equation but also the uncertainty involved in a single observation. The standard deviation of a further predicted value at the mean of the predictor variables is thus

$$\hat{\sigma}\sqrt{1 + \frac{1}{n}}$$

At station 1 for log(TSP) we thus obtain

$$\hat{\sigma}\sqrt{1 + \frac{1}{n}} = 0.1702$$

Approximate 95 percent confidence limits (in terms of proportional limits) thus becomes

$$10^{\pm(1.96)(0.1702)} = (2.16,\ 0.46)$$

That is we can predict single values with a 95 percent confidence of being within 54 percent low to 116 percent high. Thus although the regression function is well estimated, it is obvious that it is practically useless for prediction of specific single day concentrations because of the large residual error. We will now consider a situation where the regression equation can be used to advantage.

Use in Meteorological Adjustment

The previous section showed that the large residual variability precluded meaningful individual predictions of concentrations. Nevertheless, if many concentrations are predicted and then averaged, the average concentration can be estimated with dramatically improved reliability.

Suppose we use the current predictive models for a period of 1 year, for example; and that, during this year, we accumulate 100 further observations. Among differences between this year and previous years are the differences in meteorological conditions on the days for which data was obtained. If we assume that measured concentrations, then it is necessary to first remove (adjust for) these meteorological differences.

In matrix notation, we have fit the model

$$y = \beta_o + X\beta + \varepsilon$$

The estimated standard deviation of a further predicted value is given by (ref. 10)

$$\hat{\sigma}_{y \cdot x_o} = \hat{\sigma}\left[1 + \frac{1}{N} + (x_o - \bar{x})^T (X^T X)^{-1} (x_o - \bar{x})\right]^{1/2}$$

where

x_o the vector of predictor values,

$\bar{x}$ the vector of the means of the predictor values, and

$(X^T X)^{-1}$ the inverse of the normal equations matrix.

If we assume that the pollution generating process is unchanged and the only changes are in the variables, we observe (meteorologic, etc.) then, on the average, the model should correctly predict the concentrations. Hence, the quantities

$$(y_i - \hat{y}_i)/\hat{\sigma}_{y \cdot x}$$

should follow a t-distribution whose degrees of freedom are equal to the degrees of freedom available for the estimate $\hat{\sigma}$. With such large sample sizes as we have, this t-distribution is effectively unit normal distribution and hence the mean of the $(y_i - \hat{y}_i)/\hat{\sigma}_{y \cdot x}$ can easily be tested for significant difference from zero.

Degree of Improvement

We have discussed how well the models fit the data and the use of the models for prediction purposes. Now we consider the question of how much improvement has been achieved by using the estimated regressions as opposed to using the mean of the observed concentrations without any adjustment. The quantity $D = 1 - \sqrt{1 - R^2}$ where R^2 is as defined previously (i.e., the square of the multiple correlation coefficient) expresses the proportional decrease in the standard deviation of a predicted concentration when the regression equation is used as opposed to simply using the mean of the observed values. (Duncan, ref. 15, pp. 696 to 699).

From the R^2 values of table II we find that $D = 1 - \sqrt{1 - R^2}$ ranges from a low of 0.123 to a high of 0.272. Most of the R^2 values are near $R^2 = 0.40$ which gives a value of $D = 0.225$. We thus find a percent improvement of from 12.3 percent to 27.2 percent with most values near 20 percent.

Use in Source Impact Determination

One obvious application of ambient air quality data, such as the TSP data considered in this study, would be to "triangulate" back from the collected sample to the emitting source as a function of the wind direction. However, such variables as the meteorology (other than wind direction) and the relation between wind speed and ground level concentrations tend to obscure such an analysis. This section presents a possible approach to this problem based on the fact that, with the regression models just developed, it becomes possible to consider the influence of each variable separately. A different approach based on comparison of trace element "signatures" of sources compared with time and wind direction resolved TSP sampling has been described by Fordyce (ref. 16).

Among the major identified sources of TSP in Cleveland are (1) the "Flats" - a roughly ellipsoidal region on either side of the Cuyahoga River and bounded approximately by stations 1, 15, 3, and 13 and (2) two large powerplants situated along the lakeshore to the north of and slightly to either side of station 10. To illustrate how the regression models can be used to identify such sources, we examine the results for TSP at a number of stations.

Our method is as follows: (1) At each station we obtain eight estimating functions of the form $a(\text{vel})+b(\text{vel})^2$ (from $\hat{\beta}_{11}$ through $\hat{\beta}_{26}$), (2) evaluate these functions for a number of wind speeds (we limited the evaluation to wind speeds between zero and the maximum speed observed in that octant to avoid introducing errors of extrapolation), and then (3) draw contour plots corresponding to equal values of $a(\text{vel}) + b(\text{vel})^2$ using polar coordinates with the sampling site corresponding to the origin and the radial coordinate as the velocity.

As the model is formulated, when the velocity is zero the wind terms make no contribution. The estimating functions describe the observed effect of wind velocity on log(TSP) when the wind is out of each octant (and holding all of the other variables constant). The contour plots thus show a hand interpolated estimate of log(TSP) plotted against speed and direction. Positive values indicate increased concentration while negative values indicate decreased concentration. The contour plots for nine of the stations are presented in figures 2 to 10. Each plot shows the direction from the sampling site to the powerplants and the direction to the Flats. The powerplants are indicated by single arrows whereas the Flats direction is indicated by a range of directions since it is in reality a rather indistinct area source. Also indicated on the plots are the approximate distances of each of these sources from the sampling station.

Although there are some minor discrepancies, each plot indicates the direction of the sources as evidenced by "bulges" in the contours. Log(TSP) tends to decrease rapidly with increasing velocity out of directions lacking strong sources while it either increases or decreases slowly when there is a strong source upwind of the sampling station. These results are very encouraging in light of the simplicity of the model. Refinements are possible and the addition of some diffusion or transport modeling would appear to be the most promising avenues for further study.

SOURCES OF ERROR

The models we have developed utilize only the roughest of indicators of emission levels (weekly regional steel index, day of week). Hence the models are averaging over all possible emission levels which obviously contributes a significant error. However, this variability is not under control nor reducible by meteorological adjustment.

There are also considerable errors involved in the measurement and definition of the predictor variables which contribute to inadequacy of the models. Some of these errors of measurement and definition inherent in the use of the NWS climatological data are

(1) These data are for the Cleveland Hopkins Airport and have been assumed to hold for the entire city. This assumption of regional extrapolation of localized meteorology is recognized as being rather poor, particularly for a city such as Cleveland which is located on Lake Erie. The proximity of this large body of water often causes sharp temperature gradients near the shoreline, "lake breeze" fumigation incidents, and highly localized thundershower and snow squall activity.

(2) Resultant wind is a 24-hour average of direction and speed vectors. Even a casual examination of the 3-hour summaries found on the reverse side of the NWS data sheets will show wide fluctuations in both direction and speed are the rule rather than the exception.

(3) Our precipitation measure is total water equivalent of precipitation. It does not distinguish between rain or snow and drizzles or cloudbursts.

(4) Temperature is recorded only to the nearest degree.

(5) Pressure is recorded only to the nearest hundredth of an inch. Of more importance is the fact that it is a 24-hour averaged value.

Besides these errors in the meteorological data there are also model errors. For instance, we included the predictor variables x_1 to x_6 (temperature and pressure variables) because we expect that mixing conditions can be approximated from these variables. The temperatures and pressures are local ground level measurements. To predict mixing conditions, it is better to have temperature and pressure data available both for neighboring areas and at higher altitudes. Further research on predicting mixing from easily available ground level data might be of much value in determining improvements to our models. Also, we have included resultant wind velocity but no measure of directional stability. An appropriate measure of directional stability should help.

Another source of error is in the accuracy and precision of the measurement of the concentrations themselves as discussed previously in this report in the section POLLUTANT CONCENTRATION DATA.

CONCLUSIONS

We consider the results obtained to be quite encouraging with respect to the potential benefits that could come from more refined studies.

The overall results are that the mean concentration (1) increases as delta temperature increases and as its first difference decreases; (2) increases as minimum temperature increases and as the first and second differences increase; (3) increases as pressure increases; (4) generally decreases initially with increasing velocity except when there is a source upwind; (5) significantly decreased over the period of the study with a clear indication of seasonal fluctuation.

The goodness of fit of the estimated models to the data is partially reflected by the squared coefficient of multiple correlation, indicating that, at the various sampling stations, the models accounted for about 23 to 47 percent of the total variance of observed TSP concentrations. However, there is still a large variability unaccounted for so that predictions of individual values are not very helpful. (A previously published study showed that, for high volume air sampling of TSP in Cleveland, the approximate 95 percent confidence limits on the errors introduced by filters and samplers was about 12 percent high to 11 percent low.)

About a 20 percent improvement when using these equations in place of simple mean observed values is obtained when (1) predicting mean concentrations for specified meteorological conditions or (2) comparing successive yearly averages after being adjusted so as to remove meteorological effects. Considerations of the sources of error in our modeling effort indicate that this could be improved even more.

An application of the wind velocity predictor variables and their coefficients to source impact determination was presented. The results were quite resonable and indicated a potentially fruitful area for further modeling activity.

Lewis Research Center,
National Aeronautics and Space Administration,
Cleveland, Ohio, March 12, 1976,
176-90.

APPENDIX - DETAILED EXAMINATION OF THE FITTED MODELS

The results of the fits to log(TSP) at stations 20 and 21 are not included in these discussions since they have many fewer observations available.

$x_1 = \Delta T$

We define x_1 as the maximum temperature minus the minimum temperature for the 24-hour period from midnight to midnight. When the 24-hour period falls entirely within a warm high pressure cell, the temperature usually drops throughout the night achieving a minimum around dawn and then rises throughout the day achieving a maximum around midafternoon. This occurs because of radiative heat gain and loss due to clear skies. The NWS data cards do not indicate at what time of day the maximum and minimum occur. For all three pollutants, tables II, III, and IV show the coefficient of ΔT to be almost always positive and usually significantly so. Thus, as ΔT increases, the pollutant concentrations tend to increase also. It is conjectured that this is because a large ΔT tends to imply that the day experienced a high pressure system with its attendant poor mixing characteristics.

$x_2 = \Delta T'$

Although ΔT as defined is not a continuous function of time, we define x_2 as

$$\Delta T' = 3\Delta T_i - 4\Delta T_{i-1} + \Delta T_{i-2}$$

where ΔT_i is the ΔT of day i. If ΔT were a continuous function, this would be the backward noncentral first difference (up to a constant factor) and hence estimate the first derivative of ΔT (ref. 17). We feel that this variable should in some sense indicate the persistence of high and low pressure cells.

Table II shows that, for log(TSP), all of the estimated coefficients of ΔT are negative, of which three are significantly less than zero.

Tables III and IV show there are more negative than positive coefficients of x but that none are significantly different than zero.

Evidently, $\Delta T'$ is marginally useful for predicting TSP concentrations but of no apparent value in predicting SO_2 or NO_2 concentrations.

$$x_3 = \text{MIN}$$

This variable is defined as the minimum temperature for the day.

Table II shows that the estimated coefficients of x_3 for TSP are all positive with 14 of them significantly greater than zero. Tables III and IV show that this pattern does not carry over to SO_2 and NO_2. We do not have any clear explanation as to why these results are obtained. Since daily minimum temperature in Cleveland has strong seasonal characteristics, it is possible that some other variable correlated to MIN has an effect on TSP concentration but not on SO_2 and NO_2 concentrations. It is also probable that inversions and poor mixing occur more frequently in the summer months than during the winter months.

$$x_4 = \text{MIN}'$$

As with ΔT, MIN is not a continuous function of time. We however, included a derivative-like variable defined as

$$\text{MIN}' = 3\text{MIN}_i - 4\text{MIN}_{i-1} + \text{MIN}_{i-2}$$

where MIN_i is the minimum temperature on day i. Variations in minimum temperature should be related to the passage of high and low cells. MIN' should indicate this better than MIN directly because it does not involve the seasonal fluctuation of MIN.

Table II shows that all of the estimated coefficients of x_4 for TSP are positive, of which 10 are significantly greater than zero. Tables III and IV show that for SO_2 and NO_2, all the estimated coefficients are positive and there are five significantly greater than zero for each pollutant.

Evidently, MIN' is a useful predictor for pollutant concentrations.

$$x_5 = \text{MIN}''$$

This variable is essentially an extension of x_4 since it is defined as

$$\text{MIN}'' = -2\text{MIN}_i + 5\text{MIN}_{i-1} - 4\text{MIN}_{i-2} + \text{MIN}_{i-3}$$

This would approximate the second derivative of MIN if MIN were a continuous function of time.

Table II shows that all of the estimated coefficients of x_5 for TSP are positive, of which five are significantly greater than zero.

Table III shows that 12 of the 13 estimated coefficients for x_5 for NO_2 are positive of which six are significantly greater than zero.

Table IV shows that for SO_2 only 9 of the 13 estimated coefficients are positive and only one is significantly different than zero.

Evidently, MIN" is related to both TSP and NO_2 concentrations but not particularly to SO_2 concentrations.

x_6 = Barometric Pressure

This is the daily average barometric pressure in inches of mercury. High pressure cells tend to create poor mixing conditions while low pressure cells tend to create good mixing conditions.

Table II shows that 16 of the 17 estimated coefficients of x for log(TSP) are significantly greater than zero. There is one anomaly at station 9 where there is a negative slope. We have no explanation for this.

Table III shows that 12 of the 13 estimated coefficients of x_6 for NO_2 have positive coefficients with four of these being significantly larger than zero.

Table IV shows that 12 of the 13 estimated coefficients of x_6 for SO_2 are positive with five of these being significantly greater than zero.

Originally, first and second derivative-like variables for barometric pressure were included in the models, analogous to the defined differences of ΔT and MIN. It was anticipated that these variables would be important, but, on the basis of many tentative models that were analyzed, it seemed they were not.

x_7 and x_8

There have been several studies of the effect of precipitation (usually as rainfall) upon airborne pollutant concentrations. Högström (ref. 18) has reported the tendency for some gasses to "wash out" while Dana, Hales, and Wolf (ref. 3) have more recently reported that "wash out" appears to have little effect on SO_2. This is presumed to be due to chemical interactions which can involve a fairly rapid re-release of the SO_2 from the raindrops.

In this study we use total precipitation as water equivalent in inches. There may be considerable error involved in using the water equivalent of snow as if it were rain. However, there is no simple or direct way of determining from the NWS data sheets how much of the days precipitation is rain and how much is snow. The two variables x_7 and x_8 are defined as

$$x_7 = \text{total water equivalent}$$

$$x_8 = x_7^2$$

These were chosen because it was anticipated that the incremental scrubbing of pollutants by the precipitation would tend to be diminishing as the total precipitation increased. Thus, one would expect the coefficient of x_7 to be negative while the coefficent of x_8 would be a somewhat smaller and positive quantity.

Table II shows that for log(TSP) this behavior is evident for 16 of the 17 equations. All of these have at least one of the coefficients significantly different than zero except station 8. There is one distinct anomaly at station 10 where neither coefficient is significant and the pattern does not hold.

Table III shows that for NO_2, 11 of the stations exhibit the expected pattern and 5 of these 11 have at least one of the coefficients significantly different than zero. Table IV shows that for SO_2 there is no apparent pattern.

We thus find that washout clearly occurs as expected with TSP, seems to occur somewhat with NO_2 but to a lesser degree than with TSP, and seems not to occur at all for SO_2. This last result is consistent with the results of Dana, Hales, and Wolf (ref. 3).

$$x_9 = \text{Workday}$$

In order to roughly account for calendar oriented changes in human activity, we define

$$x_9 = \begin{cases} 0 \text{ for Saturday, Sunday, Federal holidays} \\ 1 \text{ otherwise} \end{cases}$$

One clearly expects concentrations to be higher for $x_9 = 1$.

Table II shows that all of the coefficients of x_9 for log(TSP) are positive with 13 of these being significantly greater than zero.

Table III shows that 11 of the 13 coefficients of x_9 for NO_2 are positive and of these one is significantly greater than zero.

Table IV shows that 11 of the 13 coefficients of x_9 for SO_2 are positive and of these one is significantly greater than zero.

x_{10} = Steel Index

The steel mills in the downtown industrial section of Cleveland are among the dominant sources of TSP and SO_2. As a rough measure of their activity, we incorporated as variable x_{10} a weekly regional steel output index from the American Iron and Steel Institute (ref. 13). The results from this are puzzling. We find that all except two of the coefficients of x_{10} for TSP are found to negative and 7 of these are significantly lower than zero. The two stations with positive coefficients are the two stations closest to the steel mills (stations 1 and 9). During the period of our study, it is known that some of the steel mills have installed controls. This may account for part of the apparent decrease in TSP concentrations with increasing output.

x_{11} to x_{21}

Wind direction, speed, and stability are known to be key factors in the transport and dispersion of pollutants. The derived variables x_{11} to x_{26} were introduced primarily as indicators of large scale or macrostability. Local ground level wind direction and velocity might be considered aspects of local transport.

The NWS punched card data summaries provide a 24-hour average vector resultant wind with velocity reported to the nearest tenth mile per hour and direction to the nearest 10° (wind from North = 0). (The reverse side of the data sheets contain the direction and speed at 3-hour intervals, but this information is not on the punched cards.) Besides this, the sheets provide a 24-hour scalar averaged speed (average amplitude) irrespective of direction.

Our method of including the resultant wind is as follows. The NWS wind direction data is rounded to the nearest 10° where 0 = North and 90 = East. We divided the compass into eight segments as in the following table:

Octant	Compass point	Degrees (from North)
1	N	340, 350, 360, 0, 10, 20
2	NE	30, 40, 50, 60
3	E	70, 80, 90, 100, 110
4	SE	120, 130, 140, 150
5	S	160, 170, 180, 190, 200
6	SW	210, 220, 230, 240
7	W	250, 260, 270, 280, 290
8	NW	300, 310, 320, 330

and associated a pair of predictor variables with each segment; namely, x_{11}, x_{12} for segment one to x_{25}, x_{26} for segment 8. For each day we then (1) determine the segment from which the resultant wind was blowing, (2) set the first x associated with that segment equal to the resultant velocity, (3) set the second x equal to velocity squared, and (4) set the x's associated with all the other segments equal to zero. For example, if the resultant wind on a particular day is 40^o from the north at v miles per hour, we then set

$$x_{13} = v$$

$$x_{14} = v^2$$

and all the other x's from x_{11} to x_{26} equal to zero.

For each pair of x's corresponding to a particular wind direction, the most likely a priori values for the coefficients of v and v^2 would be a negative coefficient of v and a smaller but positive coefficient of v^2. This corresponds to better mixing with increasing velocity combined with a "diminishing returns" type of effect. Such a function approximates the more usual form of $1/v$ which appears in diffusion models (ref. 4).

When there is a pollutant source upwind of a sampler, however, the relation of concentration to wind speed will not generally follow the aforementioned form. Dependent upon the relative sampler and source elevations, wind speed, and turbulence, fumigation (i.e., forcing of the plume to the ground) may occur. If the breeze is light, plumes can "loop" over the sampler. Increasing velocity may then bring about fumigation and thus an increase in concentration. Yet higher velocities would then increase mixing and bring about lower concentrations again. Such behavior is evidenced by the plots of figures 2 to 10 discussed in the section Use in Source Impact Determination.

x_{27} to x_{29}

In any study, such as this, which extends over a period of several years there is the possibility that there are some systematic trends in time. For example, in Cleveland, the steel mills tend to be busiest in the summer months and slowest in the late winter months. Fluctuations in the general economy would tend to have some effect on emissions due to slowing down or speeding up of emitting industries. There are also possible effects due to changes in power consumption during the year year. And, of course, there ought to be a downward trend in localities where controls have been instituted. (Box and Tiao (ref. 19) present a time series model by which the effects of such "interventions" may be evaluated.)

In this study we included only two potential trend patterns. The first is a linear drift in time (as measured in hundreds of days from Jan. 1, 1967). The second is a possible periodic trend with a period of 1 year and phase angle unspecified. These were introduced by including the variables

$$x_{27} = \frac{\text{day number}}{100}$$

$$x_{28} = \sin \theta$$

$$x_{29} = \cos \theta$$

$$\theta = \frac{\text{day number}}{365.25} 2\pi$$

Table II shows that for log(TSP) there is evidence of both a linear drop in concentration and a periodic component. All of the estimated coefficients of x_{27} are negative of which nine are significantly less than zero. At all the stations except one at least one of the coefficients of x_{28} and x_{29} is significantly greater than zero.

The variables x_{28} and x_{29} can be treated simultaneously by the mathematical identity

$$\beta_{29} \sin \theta + \beta_{29} \cos \theta = r \cos(\theta - \varphi)$$

where

$$r = \sqrt{\beta_{28}^2 + \beta_{29}^2}$$

$$\varphi = \tan^{-1} (\beta_{28}/\beta_{29})$$

the quantity r denotes the magnitude of the periodic effect and φ is the phase a angle. The following table provides the values of r and φ derived from the TSP results:

Station	Magnitude, r	Phase angle, φ, deg	Station	Magnitude, r	Phase angle, φ, deg
1	0.10	73	10	0.11	62
2	.086	60	12	.14	46
3	.15	51	14	.14	61
4	.14	51	15	.16	42
5	.11	63	16	.15	49
6	.14	51	17	.12	76
7	.15	54	18	.12	57
8	.16	53	19	.21	45
9	.049	80			

These results show that the maximum mean concentration during the year occurs roughly between mid-February and mid-March while the minimum is roughly between mid-August and mid-September. The magnitudes of the cyclic trends are all between 0.049 and 0.21 and are generally near 0.13.

Table III shows that, for NO_2, 10 of the 13 estimated coefficients of x_{27} are negative and 7 of the 10 are significantly less than zero. This shows a drop throughout the city in general. But it may be noted that all of the coefficients that are significantly less than zero correspond to stations on the East side of the city. The industrial sector is in the central part of the city distributed about the Cuyahoga River and the prevailing winds are from the west and Southwest. Thus a decrease in NO_2 emission by industry would account for such a pattern. Ten of the stations have at least one of the coefficients of x_{28} and x_{29} significantly different than zero, thus indicating a significant periodic component to NO_2 concentrations.

Table IV shows for SO_2 that 12 of the 13 estimated coefficients of x_{27} are negative and that 8 of the 12 are significantly less than zero. There has evidently been a general drop in SO_2 over the period of the study. There are six of the stations with at least one of the coefficients of x_{28} and x_{29} being significantly different than zero. There is thus some evidence of a periodic component to SO_2 data but it is not as strong as for TSP and NO_2.

Other Variables

Many other variables and combinations of variables were considered besides the ones listed here. Regression analyses were performed for many models including these other variables also. On the basis of these analyses we retained only the 29 variables listed either because of their expected importance or on the basis of high statistical significance.

REFERENCES

1. Turner, D. Bruce: Relationships Between 24-Hour Mean Air Quality Measurements and Meteorological Factors in Nashville, Tennessee. J. Air Pollution Control Assoc., vol. 11, no. 10, Oct. 1961, pp. 483-489.
2. Hales, J. M.: Fundamentals of the Theory of Gas Scavenging by Rain. Atmos. Environ., vol. 6, no.9, Sept. 1972, pp. 635-659.
3. Dana, M. T.; Hales, J. M.; and Wolf, M. A.: Natural Precipitation Washout of Sulfur Dioxide. BNW-389, Battelle-Northwest (PB-210968; APTD-1127), 1972.
4. Stern, Arthur C., ed.: Proceedings of Symposium on Multiple-Source Urban Diffusion Models. AP-86, Environmental Protection Agency, 1970.
5. Lee, E. Stanley; Sarin, S. C.; and Wang, K. M.: Parametric Time Series Modeling of Stochastic Air Pollution Data. RB-73-15, Univ. Southern Calif. (PB-23441616; PHS-AP-00895), 1973.
6. King, Robert B.; et al.: Statistical Summary of Air-Quality Data for Metropolitan Cleveland, Ohio, 1967-1972: Total Suspended Particulates, Nitrogen Dioxide, and Sulfur Dioxide. NASA TM X-3113, 1974.
7. Neustadter, H. E.; et al.: The Use of Whatman-41 Filters for High Volume Air Sampling. Atmos. Environ., vol. 9, no. 1, Jan. 1975, pp. 101-109.
8. Federal Register, vol. 36, no. 84, Apr. 30, 1971, pp. 8186-8193.
9. Searle, Shayle R.: Linear Models. John Wiley & Sons, Inc., 1971.
10. Smith, Norman R.; and Smith, H.: Applied Regression Analysis. John Wiley & Sons, Inc., 1966.
11. Daniel, Cuthbert; and Wood, Fred S.: Fitting Equations to Data. Wiley-Interscience, 1971.
12. Neustadter, Harold E.; and Sidik, Steven M.: On Evaluating Compliance with Air Pollution Levels Not to be Exceeded More Than Once a Year. J. Air Pollution Control Assoc., vol. 24, no. 6, June 1974, pp. 559-563.
13. Weekly Index of Raw Steel Production by Geographical District. American Iron and Steel Institute, 150 East 42nd St., New York, New York 10017.

14. Holzworth, G. C.: Large Scale Weather Influences on Community Air Pollution Potential in the United States. J. Air Pollution Control Assoc., vol. 19, no. 4, Apr. 1969, pp.248-254.

15. Duncan, Acheson J.: Quality Control and Industrial Statistics. 3rd ed., Richard D. Irwin, Inc., 1965.

16. Fordyce, J. Stuart.: Air Pollution Source Identification. NASA TM X-71704, 1975.

17. Collatz, Lothar: The Numerical Treatment of Differential Equations. 3rd ed., Springer-Verlag, 1960.

18. Hogstrom, Ulf: Wet Fallout of Sulfurous Pollutants Emitted from a City During Rain or Snow. Atmos. Environ., vol. 8, no. 12, Dec. 1974, pp. 1291-1303.

19. Box, G. E. P.; and Tiao, G. C.: Intervention Analysis with Applications to Economic and Environmental Problems. J. Am. Statistical Assoc., vol. 70, no. 349, pp. 70-79.

TABLE I. - DERIVED PREDICTOR VARIABLES USED IN THE REGRESSION MODELS

Variable	Symbol	Definition
x_1	ΔT	$T_{MAX} - T_{MIN}$; maximum temperature minus minimum temperature (^{o}F)
x_2	$\Delta T'$	$3\Delta T_i - 4\Delta T_{i-1} + \Delta T_{i-2}$; related to noncentral first difference of ΔT at day i
x_3	MIN	T_{MIN}; minimum temperature (^{o}F)
x_4	MIN'	$3\,MIN_i - 4\,MIN_{i-1} + MIN_{i-2}$; related to noncentral first difference of MIN at day i
x_5	MIN''	$-2\,MIN_i + 5\,MIN_{i-1} - 4\,MIN_{i-2} + MIN_{i-3}$; related to noncentral second difference of MIN at day i
x_6	B. P.	Daily average barometric pressure in inches of mercury
x_7	P_r	Total water equivalent of precipitation in inches
x_8	$(Pr)^2$	Square of x_7
x_9	WORK	Indicator of workdays versus nonworkdays $\text{WORK} = \begin{cases} 0 & \text{Saturday, Sunday, Federal holidays} \\ 1 & \text{Otherwise} \end{cases}$
x_{10}	STEEL	Weekly regional steel tonnage index
x_{11}	v_n	$v_n = \begin{cases} \text{resultant velocity; when wind is out of North octant (see appendix for complete description)} \\ 0.0\text{; otherwise} \end{cases}$
x_{12}	v_n^2	x_{11}^2
x_{13} x_{14}	v_{ne}	Similar to x_{11}, x_{12} when wind is from NE
x_{15} x_{16}	v_e v_e^2	Similar to x_{11}, x_{12} when wind is from E
x_{17} x_{18}	v_{se} v_{se}^2	Similar to x_{11}, x_{12} when wind is from SE
x_{19} x_{20}	v_s v_s^2	Similar to x_{11}, x_{12} when wind is from S
x_{21} x_{22}	v_{sw} v_{sw}^2	Similar to x_{11}, x_{12} when wind is from SW
x_{23} x_{24}	v_w v_{nw}^2	Similar to x_{11}, x_{12} when wind is from W
x_{25} x_{26}	v_{nw} v_{nw}^2	Similar to x_{11}, x_{12} when wind is from NW
x_{27}	t	Number of days from January 1, 1967 divided by 100 (Jan. 1, 1967 is nominal beginning of sampling program)
x_{28}	$\sin\theta$	$\sin(2\pi t/3.6525)$
x_{29}	$\cos\theta$	$\cos(2\pi t/3.6525)$

TABLE II. - REGRESSION

Vari-able	Symbol	Sampling								
		1	2	3	4	5	6	7	8	9
0	$\hat{\beta}_0$	-2.65	-1.23	-5.09	-2.91	-1.60	-2.21	-4.39	-4.84	3.42
1	ΔT	[b] .010	[b] .0066	[b] .010	[b] .0080	[b] .0058	[b] .0094	[b] .0096	[b] .0081	[b] .0043
2	$\Delta T'$	-.00055	-.00041	[b] -.0010	-.00034	-.00045	[b] -.00091	-.00055	[b] -.00077	-.00022
3	MIN	[b] .0037	.0018	[b] .0046	[b] .0033	[b] .0029	[b] .0034	[b] .0044	[b] .0051	.0012
4	MIN'	.00043	[b] .0021	[b] .00098	[b] .0022	[b] .0012	.00079	.00091	.0011	.00075
5	MIN''	.00044	[b] .0015	.00023	[b] .0013	.00043	.00014	.00049	.00044	.00074
6	B. P.	[b] .16	[b] .11	[b] .24	[b] .17	[b] .13	[b] .14	[b] .22	[b] .23	-.042
7	P_r	[b] -.14	[b] -.23	[b] -.17	[b] -.30	[b] -.18	[b] -.15	[b] -.16	-.11	[b] -.21
8	$(P_r)^2$	.049	[b] .10	[b] .10	[b] .16	[b] .095	.050	[b] .068	.067	[b] .080
9	WORK	[b] .076	[b] .068	[b] .049	.016	[b] .068	[b] .051	[b] .047	.014	[b] .050
10	STEEL	.00031	-.00028	-.00039	-.00040	-.00038	[b] -.0012	[b] -.00094	[b] -.0010	.00055
11	v_n	[b] -.029	.00056	.016	[b] -.040	-.012	-.027	[b] -.037	.0037	[b] -.030
12	v_n^2	.00098	-.0013	-.0010	.0019	.00005	.00074	.0016	-.0012	.0015
13	v_{ne}	-.021	-.0011	[b] .021	[b] -.045	[b] -.018	[b] .024	.0017	.026	[b] .028
14	v_{ne}^2	-.00051	[b] -.0027	-.00030	[b] .0021	-.00032	.00053	-.00030	-.00075	.00030
15	v_e	[b] -.035	-.030	.00077	[b] -.070	[b] -.057	-.028	-.011	-.00030	-.015
16	v_e^2	.0014	.00085	-.00033	[b] .0044	[b] .0031	0.0	.000090	-.0013	.00009
17	v_{se}	-.017	-.017	-.011	-.027	[b] -.024	-.024	-.0081	-.016	-.017
18	v_{se}^2	.00017	-.00019	0.0	.00065	.00042	.00052	-.00030	.00018	-.00040
19	v_s	-.0090	-.0040	-.0088	[b] -.020	[b] -.019	-.013	[b] -.018	[b] -.018	-.0036
20	v_s^2	-.00021	-.00051	-.00025	.00042	.00007	-.00010	.00004	-.00020	-.00017
21	v_{sw}	[b] -.027	-.0028	[b] -.022	-.011	[b] -.019	[b] -.015	[b] -.024	[b] -.019	.0078
22	v_{sw}^2	.00090	-.00050	[b] .00070	.00008	.00031	.00042	.00065	.00014	-.00028
23	v_w	[b] -.030	[b] -.023	[b] -.018	-.024	[b] -.017	[b] -.030	[b] -.034	[b] -.025	-.0067
24	v_w^2	[b] .0012	[b] .0013	.00049	.00099	.00067	[b] .0010	[b] .0013	.00082	.00067
25	v_{nw}	[b] -.048	-.011	-.014	[b] -.044	[b] -.022	[b] -.045	[b] -.051	-.013	[b] -.032
26	v_{nw}^2	[b] .0028	.00050	.00024	[b] .0027	.0011	[b] .0023	[b] .0028	.00029	[b] .0019
27	t	[b] -.0089	[b] -.0046	[b] -.0053	[b] -.0081	[b] -.0086	-.0011	-.0047	-.0029	[b] -.0038
28	$\sin\theta$	[b] .099	[b] .075	[b] .12	[b] .11	[b] .096	[b] .11	.12	[b] .13	[b] .049
29	$\cos\theta$	.031	.043	[b] .098	[b] .090	[b] .049	[b] .089	.087	[b] .099	.0087
	N	382	388	495	364	474	448	425	387	482
	$\overline{Y}$	2.29	1.99	2.06	2.09	2.09	1.99	1.95	1.93	2.32
	R^2	.47	.39	.47	.38	.44	.36	.42	.40	.34
	$\hat{\sigma}^2$	.0288	.0252	.0250	.0310	.0196	.0256	.0270	.0319	.0260
	$\hat{\sigma}$	.170	.159	.158	.176	.140	.160	.164	.179	.161
	D	.27	.22	.27	.21	.25	.20	.24	.23	.19

[a]These stations are not included in detailed discussions.

[b]Denotes significant coefficients.

SUMMARIES FOR log(TSP)

station									
12	13	14	15	16	17	18	19	[a]20	[a]21
-1.53	-2.75	-3.33	-5.10	-5.69	-1.10	-3.50	-4.07	-6.75	1.07
b .0083	b .0085	b .0075	b .014	b .0091	b .0069	b .0057	b .010	b .013	b .015
-.00044	-.00047	-.00046	-.00051	-.00016	-.00022	-.00025	-.00051	b -.0020	-.0017
.0021	b .0042	b .0048	b .0060	b .0043	b .0029	b .0036	b .0064	b .0077	.0030
.00053	b .0011	b .0021	.00099	b .0021	b .0013	b .0016	b .0016	-.00014	.00098
.00023	b .00074	b .0012	.00047	.00043	.00064	b .00089	.00056	.00021	.0019
b .12	b .16	b .18	b .24	b .26	b .11	b .19	b .20	b .29	.024
.027	b -.22	b -.23	b -.31	b -.19	b -.23	b -.30	b -.11	-.17	.098
-.027	b .088	b .11	b .13	b .090	b .090	b .14	b .067	.061	-.019
b .048	.027	b .034	b .049	b .048	b .046	b .043	.024	.036	b .11
-.00030	b -.00090	b -.00076	-.00009	b -.00070	b -.0011	-.00045	-.00025	-.0011	.0014
b -.040	-.015	.0050	-.0042	-.017	b -.021	-.0077	-.0064	-.050	.040
b .0025	-.00032	-.0024	-.0012	.00029	.00093	-.00063	-.00027	.0042	-.0051
-.016	.020	b -.028	-.0012	b .037	-.018	-.016	.0029	-.011	.055
.00065	b -.0023	.00078	.00053	b -.0039	.00032	-.00022	.00030	-.00078	b -.0045
b -.032	-.0056	-.011	.018	.00046	-.029	-.034	-.020	-.013	.083
.0013	-.00001	-.0022	-.0014	-.00070	-.00033	.0012	.00003	.0013	-.0089
-.0056	.0072	-.013	.013	-.0048	-.011	-.011	b -.026	-.018	b .17
-.0010.	-.00094	-.00015	-.00035	.00003	-.00042	-.00059	.00053	.0012	b -.022
-.0037	-.0096	b -.019	-.0030	-.013	-.0064	-.022	b -.023	-.0067	b .069
-.00007	-.00017	.00022	-.0011	-.00021	-.00031	.00073	.00009	.00009	b -.0043
-.0058	b -.016	-.0084	b -.031	b -.024	.0013	-.0099	b -.028	-.024	.041
.00011	.00040	-.00055	.00059	.00062	-.00058	0.0	.00045	.00077	-.0027
-.0024	b -.025	b -.018	b -.041	b -.029	b -.013	-.013	b -.025	b -.062	-.027
.00049	.00086	.00067	.0014	.00094	.00056	.00058	.00032	.0048	.0014
b -.030	b -.055	-.015	-.018	b -.030	b -.029	b -.029	-.019	b -.11	-.030
b .0020	b .0027	.00049	.00020	.0013	.0014	b .0017	.00036	b .0071	.00019
b -.0043	-.0018	b -.0035	b -.0059	-.0017	-.0020	-.0015	-.0011	-.0047	-.021
b .093	b .10	b .12	b .11	b .11	b .12	b .098	b .15	b .17	.029
.050	b .095	b .066	b .12	b .095	.029	b .063	b .15	.096	.013
483	468	443	419	438	459	445	422	112	116
2.19	1.91	1.90	2.13	1.93	2.12	1.99	1.92	1.89	2.16
.23	.41	.41	.42	.45	.42	.30	.45	.64	.62
.0358	.0251	.0247	.0543	.0281	.0211	.0273	.0277	.0264	.0407
.189	.159	.157	.233	.168	.145	.165	.166	.163	.202
.12	.23	.23	.24	.26	.24	.16	.26	.40	.38

TABLE III. - REGRESSION

Vari-able	Symbol	Sampling 1	2	3	4	5	6
0	$\hat{\beta}_0$	-43.86	7.32	-.21	-26.25	24.86	-28.48
1	ΔT	[a].085	.057	.030	[a].064	[a].050	[a].099
2	$\Delta T'$	.0018	-.0023	-.0044	.0049	.0020	-.0046
3	MIN	.0077	.0093	-.0055	.0087	-.0065	.015
4	MIN'	[a].035	[a]-.030	.0062	[a].029	.0040	[a].023
5	MIN''	[a].013	[a]-.029	.0041	[a].022	-.0058	[a].014
6	B. P.	[a]2.02	.32	.57	[a]1.54	-.30	[a]1.46
7	Pr	.26	-1.28	-1.06	-1.89	[a]-2.3	[a]-1.56
8	$(Pr)^2$	-.015	.59	.74	.91	[a]1.0	.77
9	WORK	-.015	.42	.29	.29	.32	[a].63
10	STEEL	-.0042	[a]-.023	-.0058	[a]-.025	.0020	-.0039
11	v_n	.071	.089	-.069	-.025	-.11	-.18
12	v_n^2	-.016	-.054	-.0024	-.0090	.0043	.015
13	v_{ne}	-.017	[a]-.55	-.067	-.18	-.31	[a]-.50
14	v_{ne}^2	-.0058	.027	-.00079	-.0056	.0095	[a].024
15	v_e	-.29	-.31	-.42	[a]-.49	-.45	-.33
16	v_e^2	.012	.0068	.012	[a].037	.0059	-.0081
17	v_{se}	-.17	-.18	-.019	-.38	-.20	-.095
18	v_{se}^2	.0046	-.011	-.021	.019	.00076	-.0081
19	v_s	-.20	-.19	-.23	.062	[a]-.22	-.13
20	v_s^2	.0017	.0031	.00060	-.014	.00033	-.0038
21	v_{sw}	[a]-.23	-.18	[a]-.32	.095	[a]-.33	[a]-.23
22	v_{sw}^2	.0043	-.0051	.0050	[a]-.016	.0075	.0060
23	v_w	-.14	[a]-.43	-.24	-.16	[a]-.28	[a]-.21
24	v_w^2	-.0020	.014	.0028	.0089	.0056	.0079
25	v_{nw}	-.33	-.39	[a]-.42	-.26	[a]-.56	-.14
26	v_{nw}^2	.012	.0076	.021	.012	.028	-.0058
27	t	[a]-.055	.019	.019	[a]-.12	[a]-.077	[a]-.050
28	$\sin\theta$	[a].56	.67	[a].93	[a]1.29	-.053	[a].70
29	$\cos\theta$	-.041	.58	.13	.27	-.11	.78
	N	396	177	453	333	436	390
	$\bar{Y}$	14.3	13.1	14.6	13.9	14.2	14.1
	R^2	.28	.35	.17	.32	.20	.27
	$\hat{\sigma}^2$	5.20	4.82	7.97	6.00	5.96	4.41
	$\hat{\sigma}$	2.28	2.19	2.82	2.45	2.44	2.10
	D	.15	.19	.09	.18	.11	.15

[a]Denotes significant coefficients.

SUMMARIES FOR $\sqrt{NO_2}$

station						
7	8	9	10	12	14	15
-24.58	1.10	7.17	-12.78	6.71	1.81	7.64
a .056	a .083	a .073	a .11	.039	.036	.063
-.010	-.0081	.0015	-.0052	-.0052	-.0038	-.013
-.0068	.011	.010	.0055	-.021	-.00058	.048
.0010	.0092	a .020	.013	.011	.014	.017
.0081	.011	a .012	.0073	.011	a .012	.020
a 1.45	.44	.31	1.06	.35	.50	.32
-1.55	-1.39	a -2.17	-1.44	a -2.12	a -2.72	-1.36
.10	.79	a .96	.78	.79	a 1.48	-.97
.13	.12	.24	.44	.016	.014	-.24
-.011	-.00016	-.0017	-.0092	a -.011	a -.014	-.012
a -.40	-.0015	-.28	a -.52	a -.39	.097	-.049
.019	-.015	.0098	a .035	.0086	-.024	-.036
-.085	-.086	-.14	a -.39	-.020	a -.32	-.17
-.0071	.0045	-.0030	.018	-.014	.014	.0078
-.11	-.23	a -.41	a -.45	-.097	-.39	-.37
-.0085	.0047	.011	.021	.00071	.018	.026
-.15	-.18	-.25	-.31	.065	-.23	.21
-.0036	-.0019	.0036	.011	-.012	.0016	-.025
-.098	-.071	.028	-.096	.017	a -.24	-.077
-.0063	-.011	a -.015	-.0068	-.012	.0084	-.0043
a -.28	a -.20	a -.18	a -.27	-.16	-.15	-2.3
.0048	-.0051	.0019	.0095	-.0028	-.0019	.0012
k -.16	-.11	a -.19	a -.27	a -.24	-.13	a -.62
-.0032	-.0028	.0058	.0028	.00054	-.0022	.017
a -.58	-.31	a -.39	a -.39	a -.55	-.22	-.18
.025	.010	.016	.0095	.020	.0041	-.0034
-.045	-.015	a -.10	a -.15	.00043	a -.046	-.11
.74	a .71	a .70	a .84	.35	a .51	a 1.25
a .32	a 1.09	.036	.19	.025	a .72	.94
425	413	430	340	426	384	212
14.2	13.9	15.1	15.2	13.4	12.6	14.2
.21	.23	.29	.31	.25	.20	.29
6.51	5.89	4.67	4.99	5.26	4.10	8.35
2.55	2.43	2.16	2.23	2.29	2.03	2.89
.11	.12	.16	.17	.13	.11	.16

TABLE IV. - REGRESSION

Vari-able	Symbol						Sampling
		1	2	3	4	5	6
0	$\hat{\beta}_0$	-101.4	40.71	-52.52	-14.40	3.47	-29.29
1	ΔT	[a] .15	.0030	.045	-.0057	.011	.038
2	$\Delta T'$	.0013	.015	-.0017	.0096	.0047	-.0026
3	MIN	.017	-.029	-.011	-.012	-.019	-.017
4	MIN'	[a] .048	.011	[a] .029	[a] .028	.0038	[a] .031
5	MIN''	.018	-.0086	.0077	.0094	-.011	.012
6	B. P.	[a] 3.70	-1.09	[a] 2.09	.97	.31	1.4
7	Pr	-.051	[a] 2.87	.077	-2.18	.083	-.49
8	$(Pr)^2$	.24	[a] -1.86	.18	[a] 1.95	.053	-.22
9	WORK	.33	-.042	.31	.43	.26	.25
10	STEEL	.021	.00079	.0089	-.0063	[a] .013	-.0012
11	v_n	[a] .52	-.0083	[a] .66	.00043	-.049	[a] -.52
12	v_n^2	-.038	-.030	[a] -.049	-.0061	-.014	.040
13	v_{ne}	.26	.14	[a] .60	-.41	[a] -.61	-.29
14	v_{ne}^2	-.019	[a] -.036	-.027	.014	[a] .032	.0080
15	v_e	.086	[a] -1.2	-.30	[a] -.73	[a] -1.0	[a] -.66
16	v_e^2	-.018	.046	.00089	.034	[a] .054	.026
17	v_{se}	.11	[a] -1.2	-.45	[a] -.64	-.37	-.15
18	v_{se}^2	-.0067	[a] .092	-.0015	.043	.0061	-.0056
19	v_s	-.24	[a] -.48	-.21	[a] -.32	[a] -.39	-.061
20	v_s^2	.0086	.0078	.0026	.0057	.0096	-.0059
21	v_{sw}	[a] -.33	[a] -.63	[a] -.31	-.012	[a] -.37	.032
22	v_{sw}^2	.0081	[a] .022	.0048	-.013	.010	-.0095
23	v_w	-.14	[a] -.74	-.25	-.24	[a] -.26	[a] -.36
24	v_w^2	-.0056	[a] .028	.00092	.0033	.0013	[a] .015
25	v_{nw}	.12	-.42	.28	-.32	-.41	[a] -.40
26	v_{nw}^2	-.019	.0078	-.028	.017	.021	.020
27	t	[a] -.20	.12	[a] -.10	[a] -.10	[a] -.24	-.14
28	$\sin\theta$	-.18	-.68	-.37	-.15	[a] -.72	.099
29	$\cos\theta$	[a] 1.15	.018	1.01	.63	.091	.71
	N	395	182	431	326	432	392
	$\overline{Y}$	9.78	7.31	8.06	9.49	8.75	8.11
	R^2	.31	.34	.32	.24	.27	.23
	$\hat{\sigma}^2$	11.21	6.35	8.94	6.97	7.72	6.49
	$\hat{\sigma}$	3.35	2.52	2.99	2.64	2.78	2.55
	D	.17	.19	.18	.13	.15	.12

[a]Denotes significant coefficients.

SUMMARIES FOR $\sqrt{SO_2}$

station						
7	8	9	10	12	14	15
-43.24	-34.82	-4.95	-8.24	-40.06	-33.62	-67.65
.032	.044	a .057	.052	.025	-.0099	a .084
-.0019	-.0055	.0077	.0055	-.0017	.0049	-.013
-.0040	-.0065	.016	.0049	-.025	.015	.021
.0056	.0032	.0077	.00061	.015	a .031	.030
-.0074	.0023	-.0032	.0049	.0067	.0051	a -.035
a 1.8	1.43	.48	.75	a 1.67	a 1.49	2.54
1.2	-.86	a -2.22	1.9	-.61	-.15	.86
-.49	.49	.95	-.97	.47	.65	-.70
.43	.25	a .79	.17	.37	.12	-.018
.0040	.0061	.0023	-.0025	.0018	-.0062	.013
.22	.31	a .50	-.080	-.13	-.17	-.14
-.029	-.023	a -.034	-.0072	.0045	-.0015	-.0075
.32	a .59	.031	-.30	.12	a -.42	-.028
-.0094	-.026	-.0077	.031	.00028	.020	-.012
.25	.40	-.20	-.13	.18	a -.70n	.54
-.016	-.034	.010	-.0094	-.024	.033	-.055
.17	.031	-.10	-.18	.30	a -.42	.45
-.0090	-.0027	-.00026	.0019	-.021	.013	-.031
-.038	-.11	.064	.12	-.18	a -.36	-.19
-.0042	-.0018	-.0096	-.015	.0013	.012	.0025
-.19	-.16	.14	-.069	a -.30	a -.26,	a -.45
.0044	-.00024	-.0046	.0033	.0086	.0028	.0097
-.17	-.18	.26	.15	a -.29	a -.27	a -.59
-.00008	-.0018	-.013	-.016	.0055	.0058	.011
-.14	.018	-.23	-.29	-.26	-.30	-.74
-.00060	-.011	.021	.012	.0095	.011	.035
a -.096	a -.059	a -.20	a -.30	-.024	-.046	-.079
a -.66	-.23	-.17	.50	-.23	.035	.013
a 1.2	a .90	.46	.98	.57	a 1.39	a 1.44
412	397	420	338	416	362	201
7.28	8.06	9.29	9.40	6.95	6.97	7.53
.21	.23	.21	.19	.27	.20	.31
6.44	6.35	8.46	9.75	5.49	5.78	10.28
2.54	2.52	2.91	3.12	2.34	2.40	3.21
.15	.12	.11	.10	.15	.11	.17

1 Air Pollution Control Office, 2785 Broadway
2 Audubon Junior High School, 3055 East Boulevard
3 Brooklyn Y. M. C. A., West 25 St. and Denison
4 Cleveland Health Museum, 8911 Euclid
5 Cleveland Pneumatic Tool, 3701 East 71 (near Broadway)
6 Collinwood High School, East 152 and St. Clair
7 Cudell Recreation Center, West Boulevard and Detroit
8 Estabrook Recreation Center, Fulton and Memphis
9 Fire Station 13, 4749 Broadway
10 Fire Station 19, East 55 and St. Clair
11 St. Vincent Charity Hospital, E. 22 St.
12 G. Washington Elementary School, 16210 Lorain
13 Harvard Yards, 4150 East 49 St.
14 J. F. Kennedy High School, 17100 Harvard
15 P. L. Dunbar Elementary School, 2200 West 28 St.
16 Almira Elementary School, West 98 St. and Almira
17 Fire Station 29, East 105 St. and Superior
18 John Adams High School, 3817 East 116 St.
19 J. F. Rhodes High School, 5100 Biddulph
20 St. Joseph High School, 18491 Lake Shore Blvd.
21 Supplementary Education Center, 1365 E. 12 St.

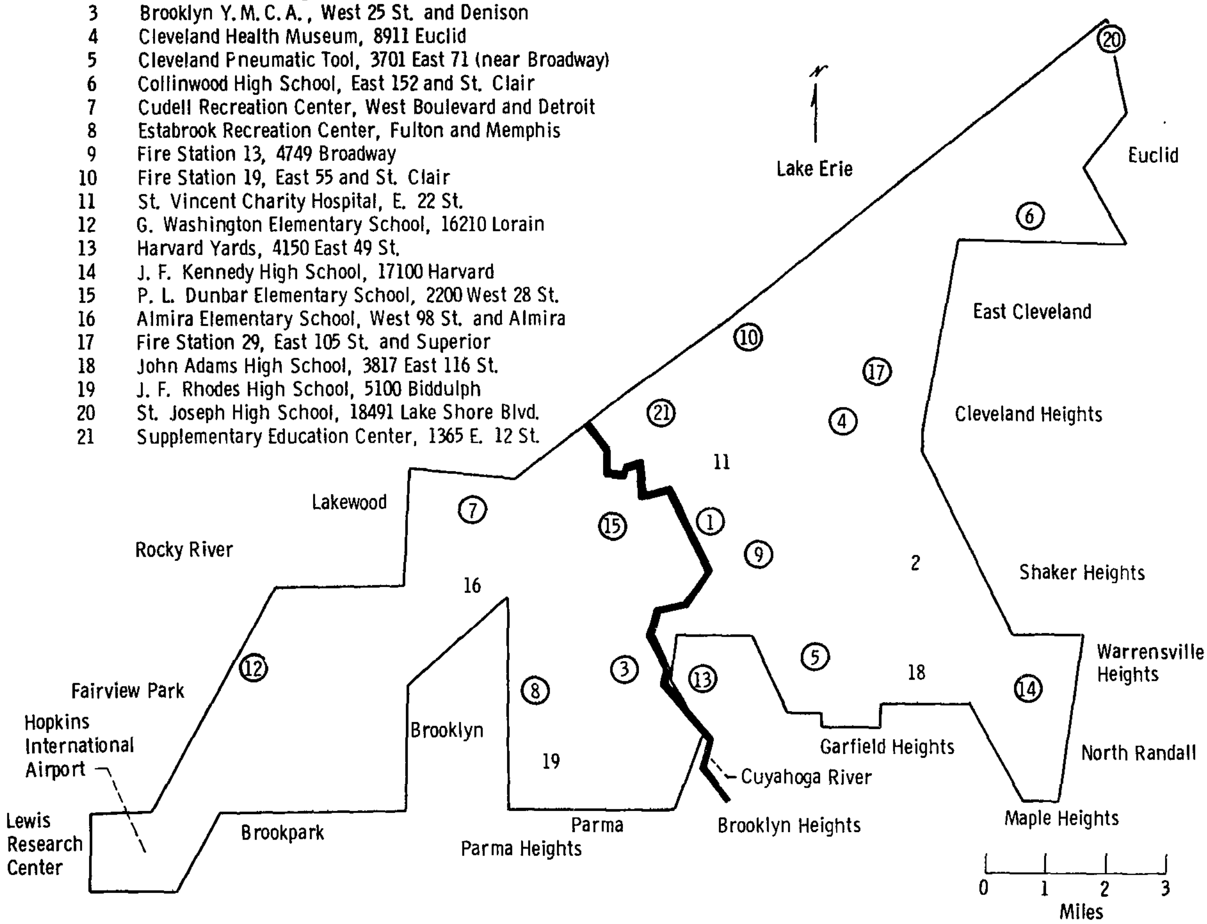

Figure 1. - Air pollution monitoring sites for Cleveland, Ohio. Municipal boundaries have been straightened somewhat but are accurate in their essential features.

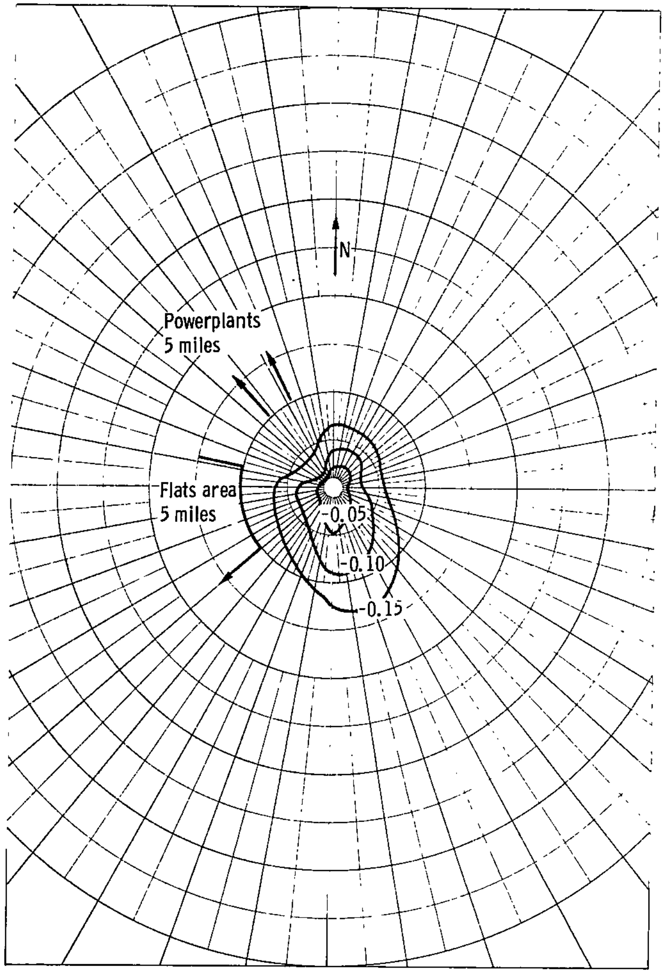

Figure 2. - Constant contours of log (TSP) against resultant wind velocity at station 2. (Angle denotes wind direction; radial scale is 1 mph/division.)

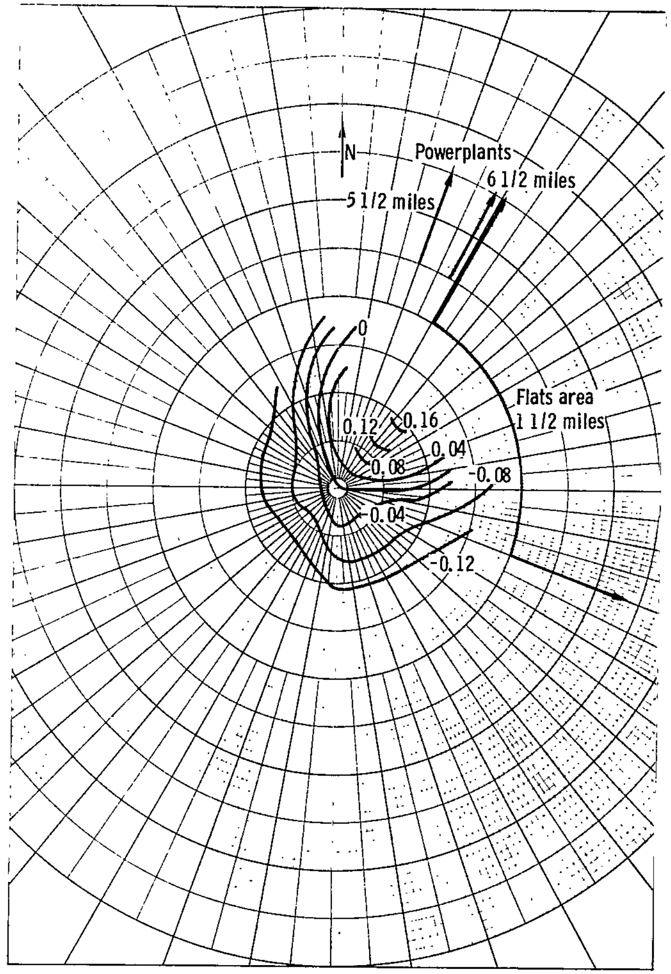

Figure 3. - Constant contours of log (TSP) against resultant wind velocity at station 3. (Angle denotes wind direction; radial scale is 1 mph/division.)

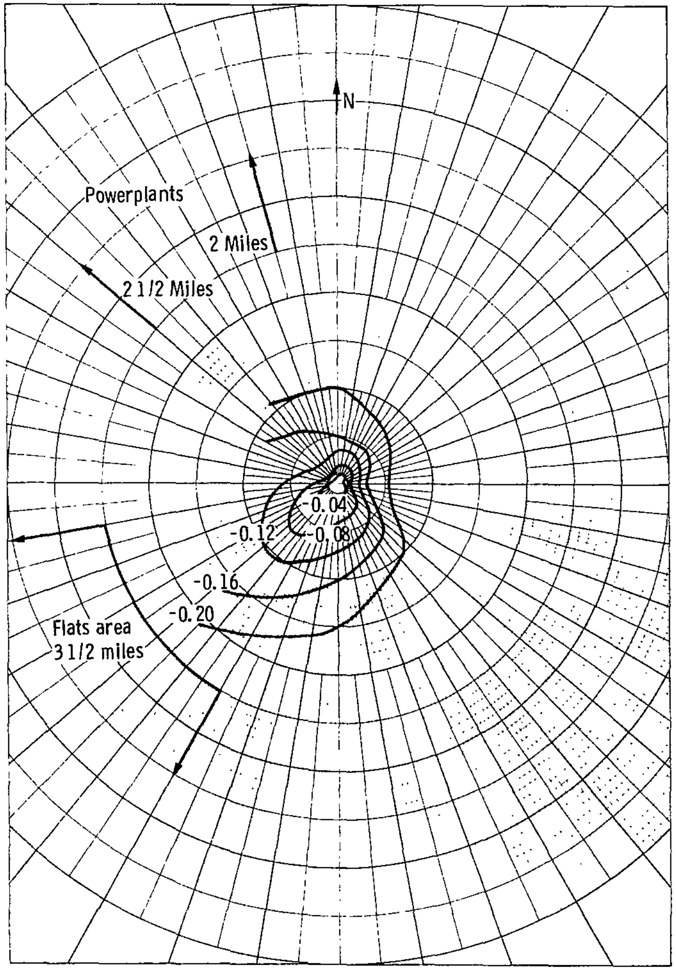

Figure 4. - Constant contours of log (TSP) against resultant wind velocity at station 4. (Angle denotes wind direction; radial scale is 1 mph/division.)

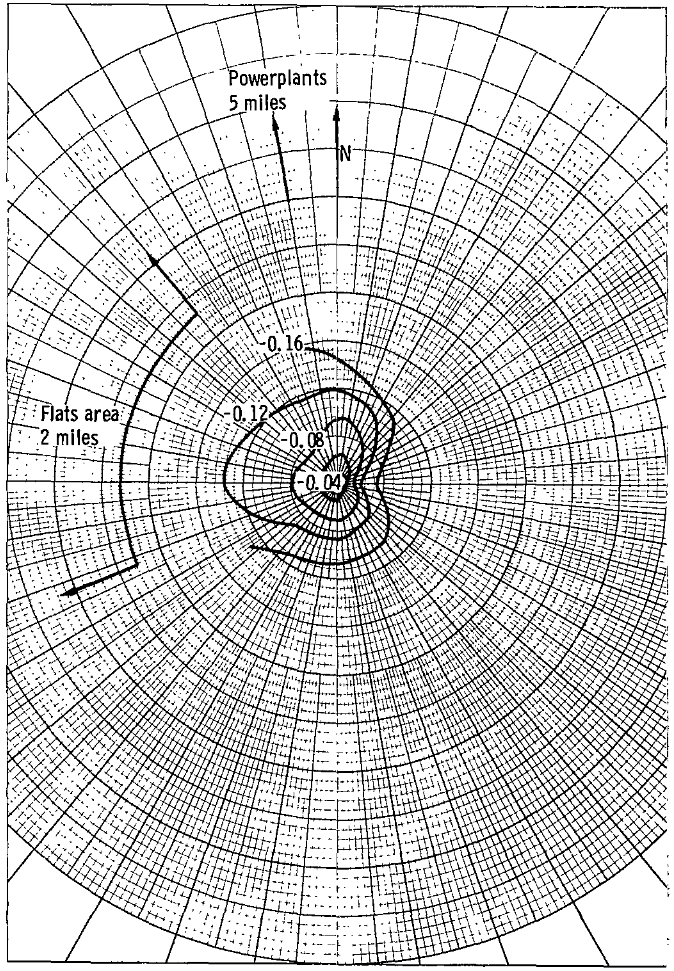

Figure 5. - Constant contours of log (TSP) against resultant wind velocity at station 5. (Angle denotes wind direction; radial scale is 1 mph/division.)

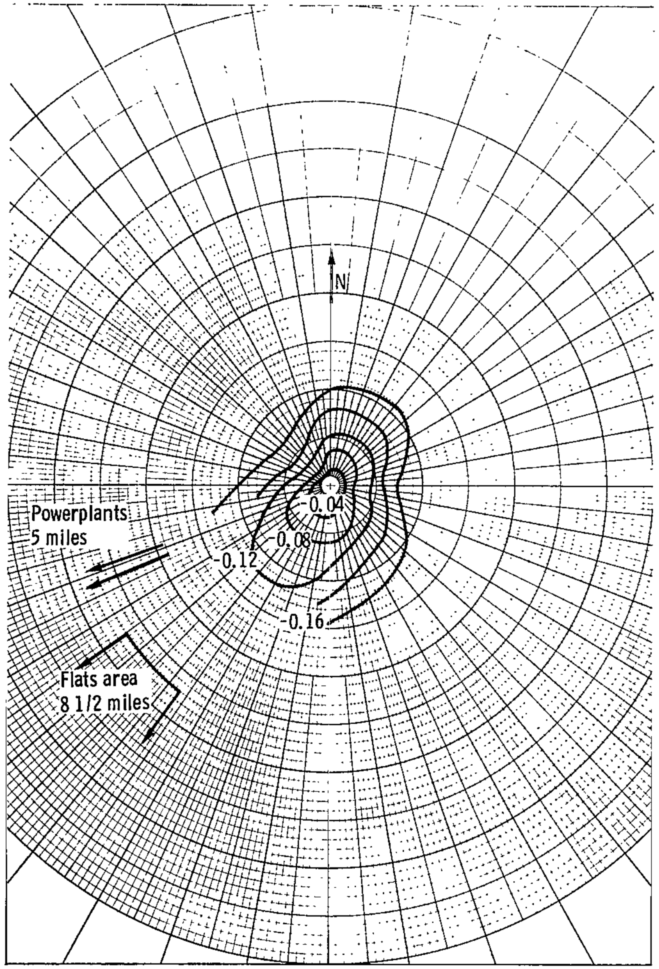

Figure 6. - Constant contours of log (TSP) against resultant wind velocity at station 6. (Angle denotes wind direction; radial scale is 1 mph/division.)

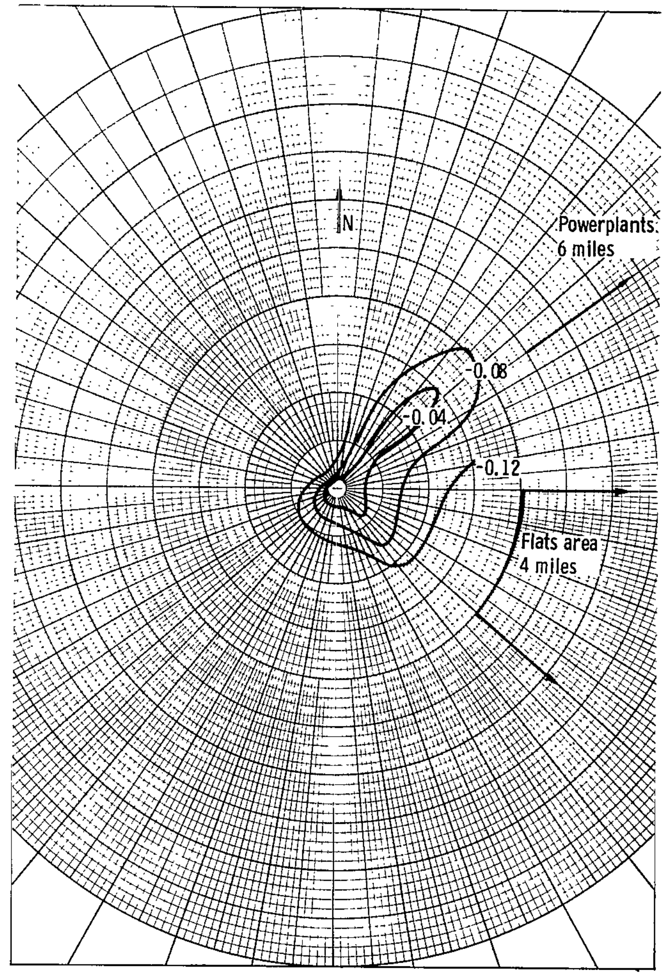

Figure 7. - Constant contours of log (TSP) against resultant wind velocity at station 7. (Angle denotes wind direction; radial scale is 1 mph/division.)

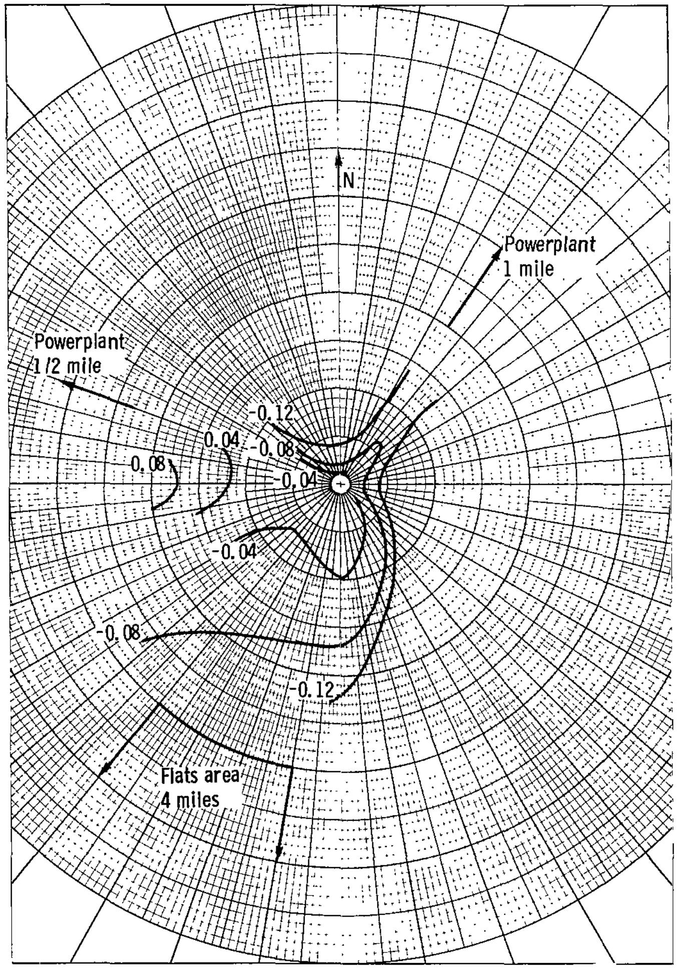

Figure 8. - Constant contours of log (TSP) against resultant wind velocity at station 10. (Angle denotes wind direction; radial scale is 1 mph/division.)

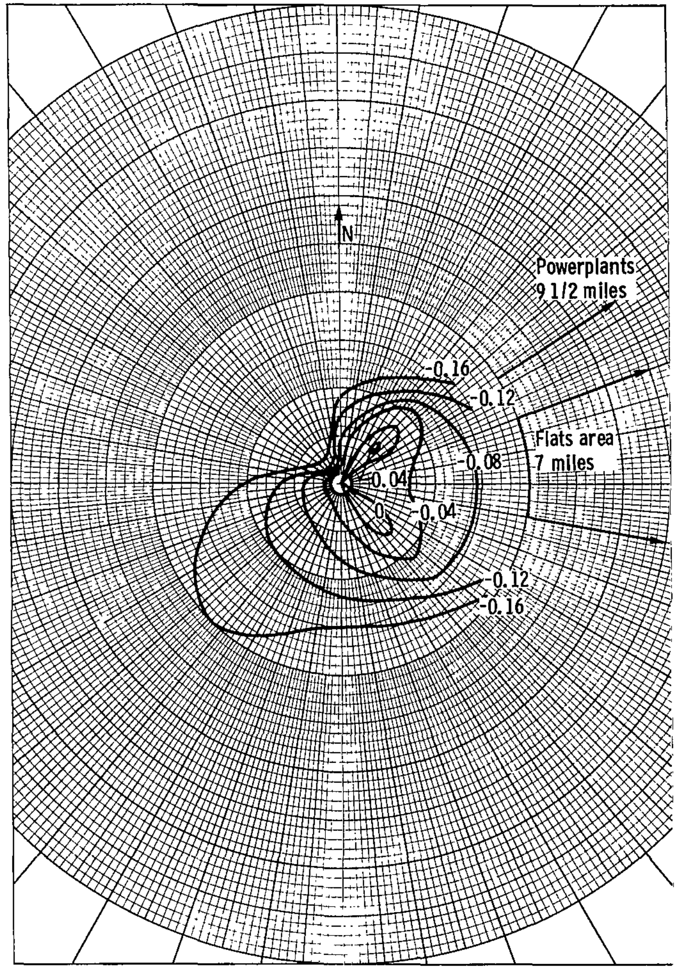

Figure 9. - Constant contours of log (TSP) against resultant wind velocity at station 12. (Angle denotes wind direction; radial scale is 1 mph/division.)

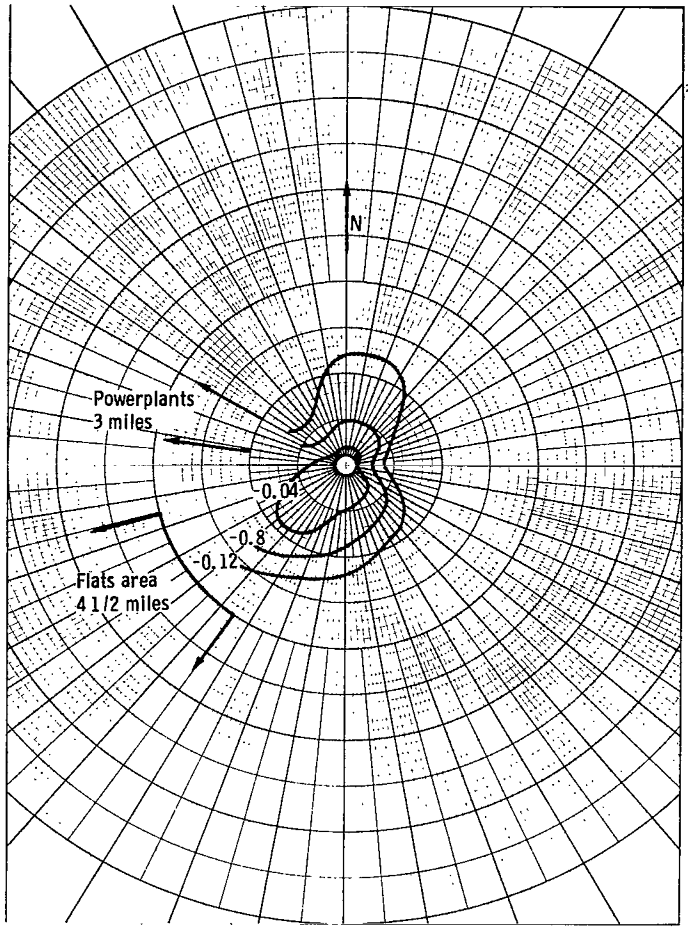

Figure 10. - Constant contours of log (TSP) against resultant wind velocity at station 17. (Angle denotes wind direction; radial scale is 1 mph/division.)

NATIONAL AERONAUTICS AND SPACE ADMINISTRATION
WASHINGTON, D.C. 20546

OFFICIAL BUSINESS
PENALTY FOR PRIVATE USE $300

SPECIAL FOURTH-CLASS RATE
BOOK

POSTAGE AND FEES PAID
NATIONAL AERONAUTICS AND
SPACE ADMINISTRATION
451

U.S.MAIL

615 001 C1 U E 760702 S00903DS
DEPT OF THE AIR FORCE
AF WEAPONS LABORATORY
ATTN: TECHNICAL LIBRARY (SUL)
KIRTLAND AFB NM 87117

POSTMASTER: If Undeliverable (Section 158 Postal Manual) Do Not Return

"The aeronautical and space activities of the United States shall be conducted so as to contribute . . . to the expansion of human knowledge of phenomena in the atmosphere and space. The Administration shall provide for the widest practicable and appropriate dissemination of information concerning its activities and the results thereof."

—NATIONAL AERONAUTICS AND SPACE ACT OF 1958

NASA SCIENTIFIC AND TECHNICAL PUBLICATIONS

TECHNICAL REPORTS: Scientific and technical information considered important, complete, and a lasting contribution to existing knowledge.

TECHNICAL NOTES: Information less broad in scope but nevertheless of importance as a contribution to existing knowledge.

TECHNICAL MEMORANDUMS: Information receiving limited distribution because of preliminary data, security classification, or other reasons. Also includes conference proceedings with either limited or unlimited distribution.

CONTRACTOR REPORTS: Scientific and technical information generated under a NASA contract or grant and considered an important contribution to existing knowledge.

TECHNICAL TRANSLATIONS: Information published in a foreign language considered to merit NASA distribution in English.

SPECIAL PUBLICATIONS: Information derived from or of value to NASA activities. Publications include final reports of major projects, monographs, data compilations, handbooks, sourcebooks, and special bibliographies.

TECHNOLOGY UTILIZATION PUBLICATIONS: Information on technology used by NASA that may be of particular interest in commercial and other non-aerospace applications. Publications include Tech Briefs, Technology Utilization Reports and Technology Surveys.

Details on the availability of these publications may be obtained from:

SCIENTIFIC AND TECHNICAL INFORMATION OFFICE

NATIONAL AERONAUTICS AND SPACE ADMINISTRATION

Washington, D.C. 20546